Final Project

The Effect of Covid-19 Lockdown on Community Currency Trade in Nairobi, Kenya

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[1879 words]

Contents

Introduction

The last decade has seen complementary currencies receive fresh attention for their potential to mitigate the problems associated with high inflation, currency volatility and external risk (Castilla-Rubio et al., 2016; Ruddick, 2019). A complementary or community currency (CC) is defined as a complementary medium of exchange to a national currency that draws on the strength of community networks in order to stimulate local economic activity with some social or environmental objective in mind (Utting, 2013). While models vary, a standard CC consists of physical vouchers or digital tokens which are issued and honoured by members of a network and can only be spent on goods and services provided by other members in the network (Bendell et al., 2015).

One of the strongest arguments in favour of CCs is that by operating parallel to national currencies, they act as a countercyclical buffer when money is scarce, such as during economic shocks (Sahakian, 2014; Sobiecki, 2018; Ruddick, 2019). An economic shock is broadly defined as a sudden and unexpected threat or opportunity caused by an unpredictable change in exogenous factors that cannot be explained by economics (Briguglio et al., 2009). Across the world, government-enforced lockdowns in response to the Covid-19 pandemic are an economic shock of devastating proportions. This paper focuses on the effect of these lockdowns on trade activity in the Sarafu Network[1], a CC system founded by Grassroots Economics in 2010. The network spans over 50 communities across Kenya, who trade daily via USSD codes to send and receive blockchain-based tokens.

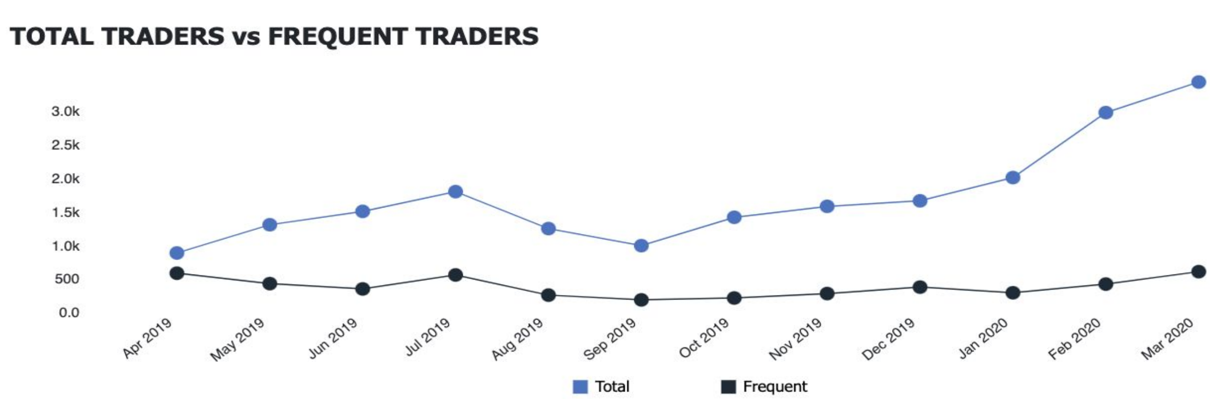

Fig 1. Increase in traders on the Sarafu Network during March 2020. Source: Grassroots Economics (2020)

[1] Note: *Sarafu* means "currency" in Swahili

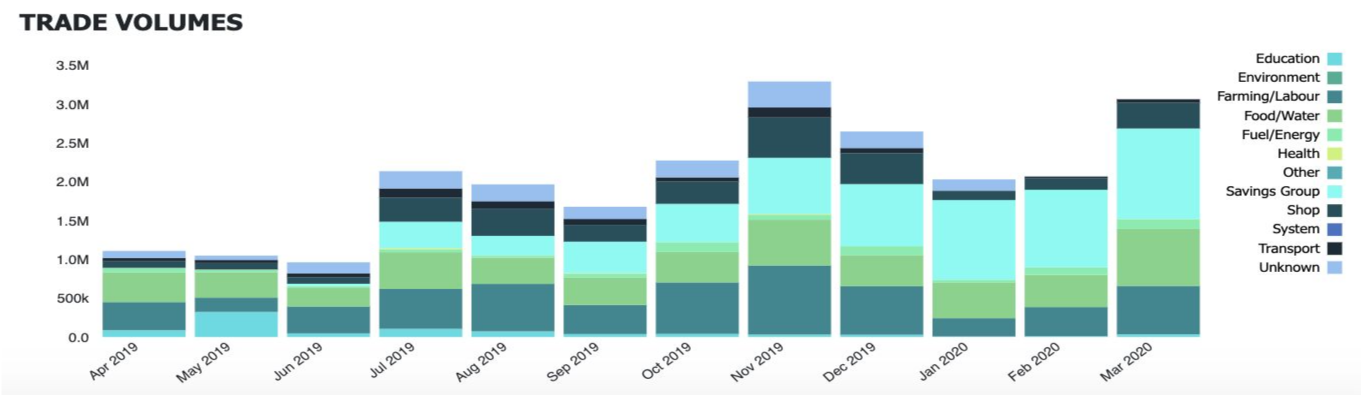

Fig 2. Increase in trade on the Sarafu Network during March 2020. Source: Grassroots Economics (2020)

According to Kiiru (2010), remittances have traditionally been used to deal with household economic shocks in low-income Kenyan communities. These shocks range from the death of a breadwinner to natural disasters. Shocks related to global events and currency volatility, however, are much harder to deal with because everyone suffers. During the Covid-19 pandemic, even remittances have run dry for many.

There is already evidence that during severe economic downturn or after high-spending periods such as the December festive season, people are more likely to spend their CC tokens as they try to save what little national currency they have (Ruddick, 2019). During a time like this, one would expect trade volumes to spike, as seen in Fig. 1 and Fig. 2, because more business owners are likely to accept payments partially in CC tokens in order to maintain profits.[2] The question left to ask is how to quantify the impact of an economic shock like Covid-19 lockdown on trade. This paper will analyze CC daily trade volumes for pre- and post-lockdown periods in Nairobi, comparing the effect of lockdown to a synthetic control.

[2] **#evidencebased:** This introduction lays out the theoretical and analytical evidence that community currencies may have an important role to play in buffering the effect of economic shocks. Data from the Sarafu network is included to show what might be a plausible trend. This evidence sets up the central argument in my thesis and logically leads to the question I proceed to explore in the paper: How we might quantify the impact of the countercyclical buffer effect of CCs by analyzing a counterfactual using synthetic control methods?

Data

The data for this study is publicly available on the Grassroots Economics website. There are 85,176 observations for trades placed on the Sarafu Network between 25 January 2020 and 14 April 2020 with information on the timestamp, blockchain hash of the sender and receiver, gender, community token name, purpose of the trade and trade amount. The main challenge was modifying the data into a panel dataset in order to control time-invariant confounders between daily observations grouped by location. Data preprocessing included dropping transactions for reclamation of tokens between users and the system; categorically encoding the location and purpose of each transaction; and combing through the often misspelt variations of the names of locations[3]. The dataset was reduced to 81 daily observations for 43 locations around Kenya, with variables for daily trade volume, gender ratio (the proportion of females to males in daily trading activity), number of daily trades, number of new users, and main purpose such as paying for food, education or transport.

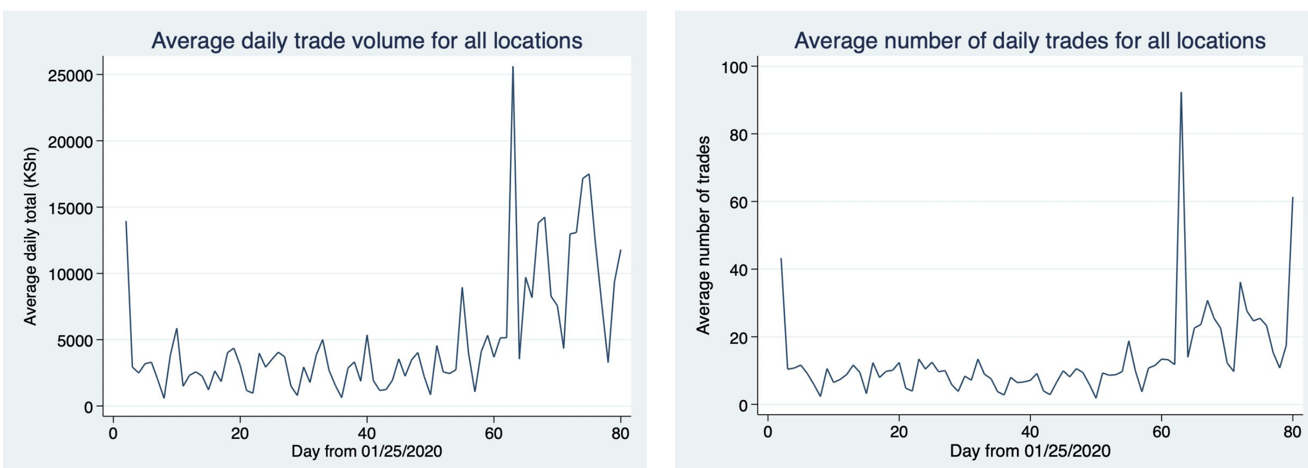

Fig. 3 Average daily trade volume and average number of daily trades on the Sarafu Network.

[3] Note: It cannot be emphasized just how important this step is. When dealing with user-inputted data, the same location might appear as "Kibandaongo", "Kibandaogo", "kibandaongo" and "Kibandadogo". Interestingly, I found a 2007 Elections Register Gazette to be profoundly helpful as most voting stations happened to be schools named after the village or area they were in, and this helped me easily match obscure "un-Googleable" location names to their respective cities and counties. Who would have thought there are slums in Nairobi called "Australia", "Bangladesh" and "Congo"?

Fig. 3 shows a clear trend in increase in trade volume around the time of Covid-19 lockdown. The large standard deviations in Table 1, however, indicate there is great variation in the data, supporting the use of a unit-weighted synthetic control.[4]

Table 1. Summary statistics for daily trade volume		
Variable	Mean	Standard deviation
Daily total (KSh)	6072.41	76330.61
Gender ratio (buyers)	0.82	2.02
Gender ratio (sellers)	1.04	2.67
Number of daily trades	14.85	134.72
Number of new users per day	0.89	7.82
Main trade purpose	7.83	3.12

Table 1: Summary statistics reported for all locations (3,483 observations)

One limitation of the data is that there were very few explanatory variables to capture demographic-related factors such as age or education. This posed a serious challenge for establishing comparability between treatment and control units because transaction data alone potentially omits dozens of confounding variables. A labour-intensive solution to this problem was to find "data about the data" as a proxy for unavailable information. For each daily observation for each location, it was possible to extract the ratio of females to males in people who made and received purchases ; the most popular trade category for that day, the number of trades placed, and the number of new users who joined the network. This kind of information gives us some idea about the gender balance of business ownership in an area, its main economic sector, and the general amount of economic activity that occurs there.[5] Table 2 shows the final list of variables used in the model.

[4] Note: Summary statistics for daily trade volume by location can be found in Appendix A.

[5] **#constraints/#variables:** The constraints of the available data are clearly outlined and elaborated on here and in the "Limitations" section. The main issues encountered were a) the less-than-ideal format of the data and b) a lack of explanatory variables I show in detail how I overcame format obstacles and address constraints by first transforming the data and manually sourcing missing information. I then scrutinized the data for proxy trends – information that might be substituted for more direct, available data. This creates a set of suitable independent variables to use in the model. All this required extra work (at least 8+ hours) in the data cleaning and processing stage, yet the result was a significantly more nuanced panel data to bolster the external validity of the results.

Table 2. Dependent and independent variables	
Dependent variable	Independent variables
Daily trade volume (> week 11)	Daily trade volume (weeks 1-11)
	Trade purpose (weeks 1-11)
	Buyer gender ratio (weeks 1-11)
	Seller gender ratio (weeks 1-11)
	Number of trades (weeks 1-11)
	Number of new users (weeks 1-11)

Table 2: Variables used in the synthetic control model, with each independent variable fixed at weekly periods

Method

To evaluate the effect of Covid-19 lockdown on trade volume in Nairobi, the central question is how trade volume would have evolved in Nairobi after 25 March 2020 in the absence of the lockdown.
The synthetic control method developed by Abadie et al. (2010, 2015) and Abadie and Gardeazabal (2003) provides a systematic way to estimate this counterfactual. This method is based on the belief that when there are a number of aggregate units being analyzed (such as cities, states of countries), a combination of these comparison units (the “synthetic control”) does a better job of reproducing characteristics of a treated unit than using a single comparison unit alone (Cunningham, 2018). An ideal synthetic control nearly perfectly satisfies the parallel trends assumption. While Difference-in-Differences methods allow for some variation in the pre-treatment trends of treated and control units, the synthetic control ought to produce an exact pre-treatment replica because it is the closest construction of a realistic counterfactual.

Locations omitted from the donor pool are Kwale, Kilifi and Mombasa, as these areas also received Covid-19 lockdown. The number of pre-treatment periods included in the model are taken weekly from day 7 (2 February 2020) through day 77 (12 April 2020) in order to minimize bias in the data. The advantage of this approach is that it allows effects of confounding unobserved characteristics to vary with time (Abadie et al., 2010). Table 3 shows the unit weights used to build the synthetic control.

Table 3. Synthetic control unit weights	
Control Unit *(Code / Name)*	Unit Weight
(0) Chidzivuni	0.024
(24) Miyani/Mnkanyeni	0.487
(25) Mkanyeni	0.134
(27) Mwangaraba	0.317
(38) Yowani	0.037

Table 4 compares the pre-treatment characteristics of Nairobi with its synthetic counterfactual, as well as with the population-weighted average of the 39 other areas in the donor pool. For simplicity, only values for day 70 and 77 are shown, however the model uses all weekly periods. It is clear that the average of areas that did not receive lockdown does not provide a suitable control group for Nairobi. Unfortunately, the synthetic control does not appear to be a perfect match either, suggesting that there are unobservable confounding variables in the data related to the number and volume of daily trades and the gender balance of business owners (the synthetic control appears to have more female sellers).

Table 4. Daily trade volume predictor means			
	Nairobi		Average of 39 control areas
Variables	Real	Synthetic	
Daily trade total(70)	47531	62099.97	7846.55
Daily trade total(77)	221239	14540.54	6987.21
Main trade activity (70)	3 (Food/Water)	3.02 (Food/Water)	7.09 (Retail)
Main trade activity (77)	3 (Food/Water)	3 (Food/Water)	7.20 (Retail)
Buyer gender ratio (70)	2.10	2.17	0.87
Buyer gender ratio (77)	1.14	2.98	0.61
Seller gender ratio (70)	1.81	4.79	1.04
Seller gender ratio (77)	1.01	2.83	1.39
Number of daily trades (70)	121	40.88	9.39
Number of daily trades (77)	289	46.8	13.05
Number of new users (70)	0	3.85	0.5
Number of new users (77)	0	2.55	0.5

Results

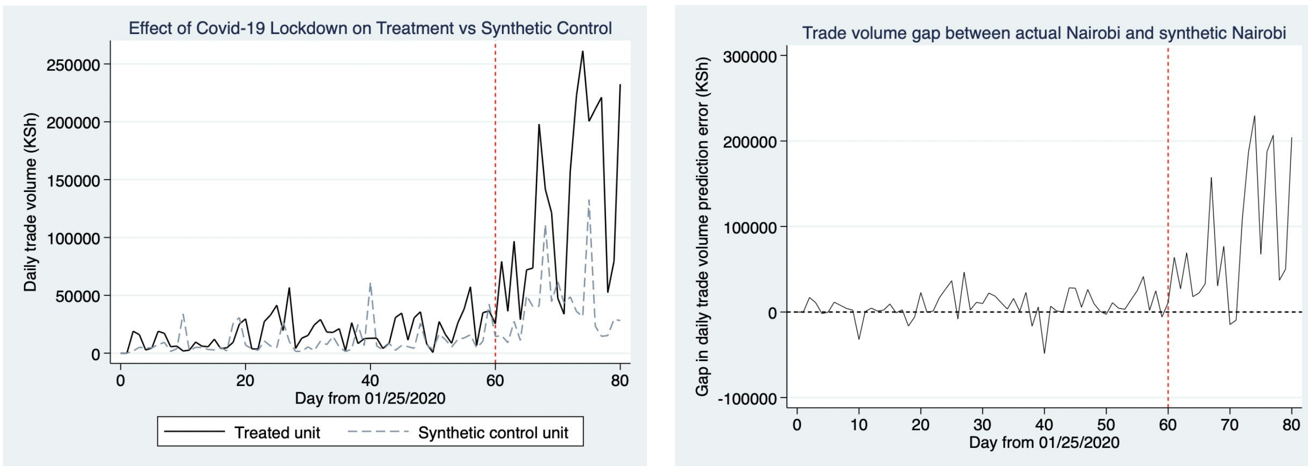

Fig. 4. Pre- and post-treatment trends for trade volume (total and gap) in Nairobi vs its synthetic control

Fig. 4 shows that there is a slight increase in daily trade volume for the synthetic control. Consequently, the gap in daily trade volume between Nairobi and the control does not show a sharp discontinuity between the pre- and post-treatment periods. According to these results, Nairobi has experienced a spike in trade volume of up to KSh200,000 (USD 1,867.94) more than its synthetic control. This is promising because it means that the alternative currencies people are using to pay for goods and services is money that otherwise would not have circulated during this time. For small business owners, this additional income can be a lifeboat.

However, the fact that the synthetic control also increases may be attributed to the fact that although other areas did not receive lockdown, Covid-19 has still had a widespread effect on the entire nation, causing a simultaneous increase in volume in all communities. The overall effect of Covid-19 in Kenya may distort the distinction between areas that receive lockdown and those that do not. It is therefore impossible to isolate a perfect treatment assignment because in some way or another, everyone is economically affected. For example, the Kenyan Shilling has depreciated in value relative to the US dollar, government-funded employment opportunities are more scarce as more money goes towards healthcare, and schools are closed so teachers are not receiving salaries.

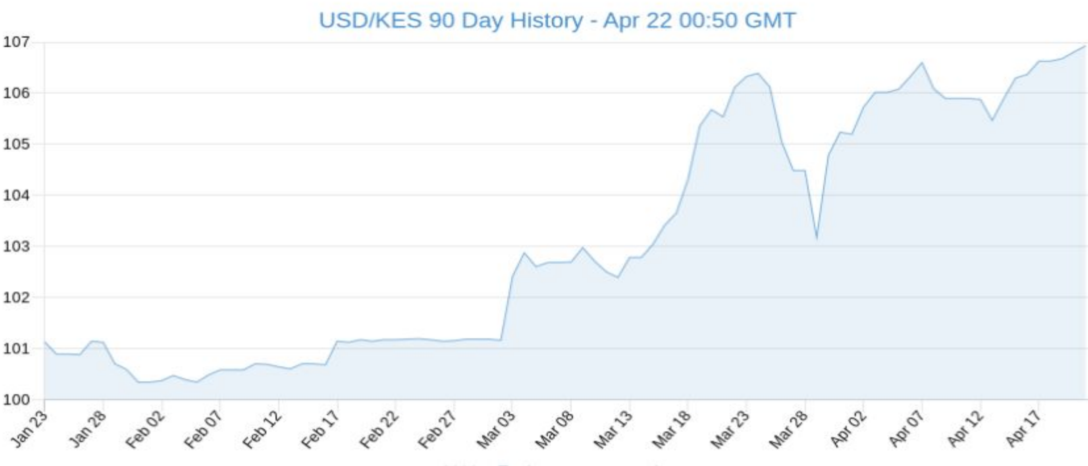

Fig. 5 USD to KSh exchange rate from 01/23/2020 to 04/17/2020 Source: Exchange Rates UK (2020)

Unit weights in the synthetic control model are selected according to the distribution of ratios of post-to-pre treatment root mean squared prediction errors (RMSPE).

$$RMSPE = \left(\left(\frac{1}{T-T_0}\right)\sum_{t=T_0+t}^{T}\left(Y_{1t} - \sum_{j=2}^{J+1} w_j^* Y_{jt}\right)^2\right)^{\frac{1}{2}}$$

This formula compares the treatment to counterfactual state for each time period (Cunningham, 2018). By iterating through this process for each unit for both pre- and post-treatment periods each location has its own placebo treatment and counterfactual. The ratio of the post-to-pre treatment RMSPEs is then sorted in descending order, with higher values indicating the treatment effect is more extreme relative to the other placebos. Since Nairobi only ranks 6^{th}, its ratio in the distribution $= \frac{RANK}{TOTAL} = \frac{6}{40} = 0.15$. This tells us that ultimately, these results are not statistically significant. However, their economic significance arguably still stands. The general increase in trade volume and new traders across all locations (seen in Fig. 3) is most likely a response to the nation-wide effect of Covid-19. This trend supports the hypothesis that community currencies are a useful tool for buffering economic shocks.[6]

[6] **#significance:** I show how the statistical significance in the model is derived and discuss its implications and discuss how practical, economic significance is still applicable.

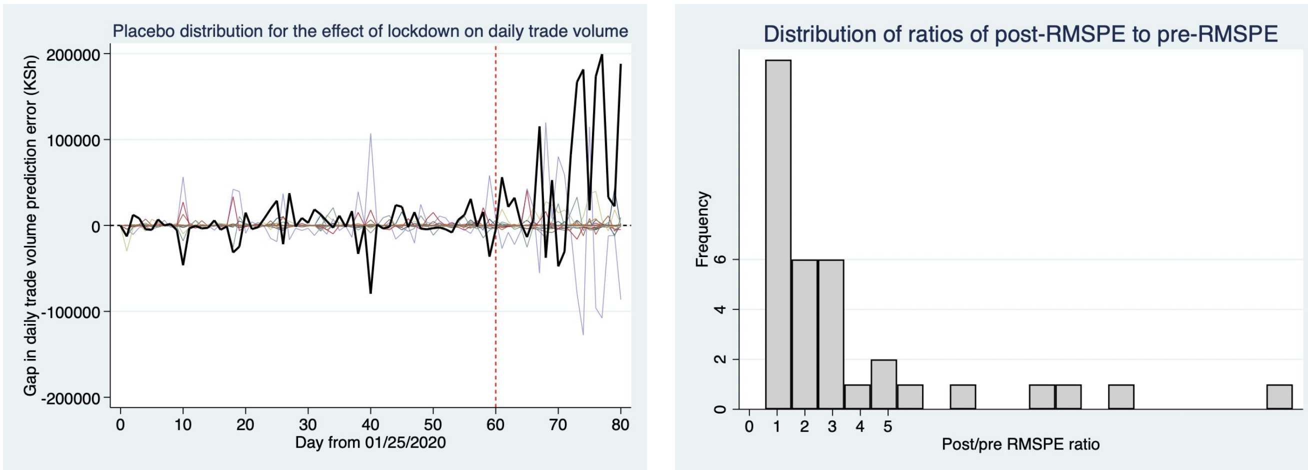

Fig. 6 Synthetic control placebos for each location pre- and post-treatment (left), based on ratios of the post-to-pre treatment RMSPE amongst control units (right). In the first graph, the bolded line shows daily volume in Nairobi, which remains considerably higher than in location that did not receive lockdown. In the second graph, Nairobi is the furthermost bin and the preceding 5 bins are the units included in the synthetic control.

Limitations

While the results show some notable differences in daily trade volume between regions, it is undeniable that this dataset suffers from a lack of explanatory data. This highlights the constraints on inferring causality based on non-experimental data, where no predefined program or study has necessitated the collection of auxiliary data such as regional demographics and socio-economic conditions. Spending behaviour between regions is only comparable to a certain degree; in reality, there are a host of unobserved factors that may affect a difference in trends.

Another concern is that the treatment under consideration, curfew restrictions due to the Covid-19 pandemic, may not be universally applied to units labelled as the treatment group. While Nairobi is a bustling capital city and has seen considerable police presence to enforce the curfew, it is impossible to tell to what extent the treatment differs from the control units. It is hardly likely that police are patrolling the streets as in places like Italy, least of all in dense slum communities. Instead, the treatment in this case is best interpreted as the combination of the effects of curfew: the knowledge of there being a curfew and the fear of punishment along with closed stores and a general slowdown in economic activity.[7]

It can best be said that this project was an exercise on finding causal effects when working with very tricky and messy data. The importance of this is often overlooked in the field of econometrics. While large, cleaned datasets exist for well-known programs, this is often not the case when working with highly specific, contextual studies. The motivation to work with this data nonetheless is that not all empirical economic phenomena can be analyzed through the neatly-packaged lens of a well-funded program. It would be a shame to not study things simply because they're too difficult and inconvenient to analyze. The challenge to economists who are interested in non-conventional economic models is that proving they are worth studying, debating or implementing requires a skillful ability to translate what is disorganized or incomprehensible in a language that others can understand. The results may not be perfect, the statistics a little off, but the exercise itself moves the field one step closer to understanding an economic phenomenon that someone else may choose to look at.

Conclusion

The Covid-19 pandemic has exposed the fragility of economies that share risk through interdependent currencies and global supply chains. At a hyper-local level, there is an urgent need to provide adequate social protection policies for communities that are vulnerable to economic shocks. More sobering, perhaps, is the reality that in many regions around the world, these "shocks" are not a once-in-a-blue-moon occurrence but a perpetual state of currency scarcity and economic stagnation. Community currencies offering a promising model to address this by providing people with an alternative when national currency is no longer available. Evidence from the increase in trade on the Sarafu Network due to Covid-19 lockdown in Nairobi suggests that these currencies can be extremely useful as a countercyclical buffer.

[7] **#context/#critique:** In this section and throughout the paper, I provide plausible explanations for why the results are not entirely robust. I discuss a) the general economic effects of Covid-19 in Kenya and b) the potential lack of enforcement of treatment. The interplay between these two factors makes it very difficult to infer direct causality, yet understanding the overall context of the current socio-economic situation still supports the argument that community currencies can act as buffers.

References[8]

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Kiiru, J. M. (2010). Remittances and Poverty in Kenya. OIDA International Journal of Sustainable Development, Vol. 1, No. 8, pp. 33-41

Republic of Kenya. (February 23, 2007). *The Kenya Gazette*. Volume CIX No. 18.

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[8] **#sourcequality:** I have extensively researched the topic of community currencies and buffer effects from a number of economic journals and peer reviewed publications. Because this is such a nascent field, many of these sources are written by known practitioners and therefore are the most appropriate source of authority on the topic. In addition, all the data I use is fetched directly from the network I wish to study.

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Appendix A: Data

Before conversion to panel data format:

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T
1	id	timeset	transfer_sub	transfe	source	s_comm_tkn	s_ge	s_location	s_business_t	target	t_comm_tkn	t_gender	t_location	t_business_	tx_token	weight	tx_hash	type	token_name	token_addre
2	1	13:17.7	DISBURSEMENT		0xBDB3Bc88	None		None	System	0x245fc81fe	None	female	GE Office	Savings Group		18000	no hash foun	directed	Sarafu	0x0Fd6e8F23
3	2	13:19.1	DISBURSEMENT		0xBDB3Bc88	None		None	System	0xC1697C132	None	male	GE Nairobi	Farming/Labour		9047.66089	no hash foun	directed	Sarafu	0x0Fd6e8F23
4	3	13:20.3	DISBURSEMENT		0xBDB3Bc88	None		None	System	0xBAB77A20	None	male	GE Nairobi	Farming/Labour		25378.726	no hash foun	directed	Sarafu	0x0Fd6e8F23
5	4	13:21.5	DISBURSEMENT		0xBDB3Bc88	None		None	System	0xD95954e3	None	male	G.E	Farming/Labour		4495.93258	no hash foun	directed	Sarafu	0x0Fd6e8F23
6	5	48:43.0	DISBURSEMENT		0xBDB3Bc88	None		None	System	0x4AB73Cfa	None	male	Home	Farming/Labour		400	no hash foun	directed	Sarafu	0x0Fd6e8F23
7	14	34:16.7	DISBURSEMENT		0xBDB3Bc88	None		None	System	0x4AfD04b9	None	male	Test	Health		400	no hash foun	directed	Sarafu	0x0Fd6e8F23
8	19	32:36.5	DISBURSEMENT		0xBDB3Bc88	None		None	System	0xeFad5486	None	male	Gatina	Food/Water		621.689801	no hash foun	directed	Sarafu	0x0Fd6e8F23
9	20	32:38.0	DISBURSEMENT		0xBDB3Bc88	None		None	System	0x66878365	None	male	Gatina	Shop		714.378298	no hash foun	directed	Sarafu	0x0Fd6e8F23
10	21	32:39.4	DISBURSEMENT		0xBDB3Bc88	None		None	System	0xD239dc57	None	female	Gatina	Food/Water		268.709888	no hash foun	directed	Sarafu	0x0Fd6e8F23
11	22	32:40.8	DISBURSEMENT		0xBDB3Bc88	None		None	System	0xD6766d64	None	female	Gatina	Shop		499.631281	no hash foun	directed	Sarafu	0x0Fd6e8F23
12	23	32:42.2	DISBURSEMENT		0xBDB3Bc88	None		None	System	0xaA7Fd999	None	female	congo	Food/Water		694.614875	no hash foun	directed	Sarafu	0x0Fd6e8F23
13	24	32:43.5	DISBURSEMENT		0xBDB3Bc88	None		None	System	0x7002Fde3	None	female	congo	Shop		2819.65507	no hash foun	directed	Sarafu	0x0Fd6e8F23
14	25	32:45.1	DISBURSEMENT		0xBDB3Bc88	None		None	System	0x27175679	None	female	congo	Farming/Labour		223	no hash foun	directed	Sarafu	0x0Fd6e8F23
15	26	32:46.4	DISBURSEMENT		0xBDB3Bc88	None		None	System	0xfDa3ab16	None	female	congo	Farming/Labour		556.678592	no hash foun	directed	Sarafu	0x0Fd6e8F23
16	27	32:47.6	DISBURSEMENT		0xBDB3Bc88	None		None	System	0xdfe2C99A4	None	female	bangladesh	Food/Water		1028	no hash foun	directed	Sarafu	0x0Fd6e8F23
17	28	32:49.0	DISBURSEMENT		0xBDB3Bc88	None		None	System	0xE2982a68	None	female	Bangla	Food/Water		1063	no hash foun	directed	Sarafu	0x0Fd6e8F23
18	29	32:50.5	DISBURSEMENT		0xBDB3Bc88	None		None	System	0x7bA9716b	None	male	bangladesh	Farming/Labour		432	no hash foun	directed	Sarafu	0x0Fd6e8F23
19	30	32:52.3	DISBURSEMENT		0xBDB3Bc88	None		None	System	0x33ef718d4	None	male	Kangemi	Farming/Labour		690	no hash foun	directed	Sarafu	0x0Fd6e8F23
20	31	32:53.7	DISBURSEMENT		0xBDB3Bc88	None		None	System	0x3c77Ab27f	None	female	Lindi	Food/Water		514	no hash foun	directed	Sarafu	0x0Fd6e8F23

After conversion to panel data format (data cleaning processed using Python):

	A	B	C	D	E	F	G	H
1	date	location	daily_total	gender_ratio	gender_ratio	main_purpos	n_trades	n_new_users
2	0	0	0	0	0	10	0	0
3	1	0	0	0	0	10	0	65
4	2	0	100	1	1	6	1	0
5	3	0	0	0	0	10	0	0
6	4	0	0	0	0	10	0	0
7	5	0	0	0	0	10	0	0
8	6	0	5	1	1	3	1	0
9	7	0	830	0.5	2	3	3	0
10	8	0	0	0	0	10	0	0
11	9	0	202	2	2	3	3	0
12	10	0	0	0	0	10	0	0
13	11	0	300	0.5	0.5	3	3	0
14	12	0	0	0	0	10	0	0
15	13	0	0	0	0	10	0	0
16	14	0	0	0	0	10	0	0
17	15	0	400	1	1	3	1	0
18	16	0	200	1	1	6	1	1
19	17	0	0	0	0	10	0	0
20	18	0	1000	1.33333333	0	3	7	0

Summary statistics for daily trade volume by location:

Unit	Obs	Mean	Std. Dev.	Min	Max
0	81	668.9259	1529.618	0	9530
1	81	9.876543	88.88889	0	800
2	81	752.5235	1125.714	0	7870
3	81	59.71605	193.9472	0	910
4	81	426.8272	997.9642	0	6000
5	81	118492.5	479303.1	0	4267536
6	81	428.7531	1043.492	0	5600
7	81	9.876543	62.45986	0	400
8	81	4.938272	44.44444	0	400
9	81	31.48148	110.2396	0	800
10	81	37.03704	109.7662	0	400
11	81	367.5432	840.1389	0	5360
12	81	28.2716	81.75864	0	400
13	81	11158.82	19514.09	0	164115
14	81	11.49383	57.55978	0	385
15	81	8.024691	52.11573	0	400
16	81	28616.05	27017.64	0	155656.1
17	81	24.83951	102.8605	0	634
18	81	2827.037	6374.393	0	48602
19	81	1.259259	7.806692	0	50
20	81	4.320988	38.88889	0	350
21	81	7.654321	49.04772	0	360
22	81	2.469136	22.22222	0	200
23	81	3.08642	16.48044	0	100
24	81	31556.18	42655.58	0	237041
25	81	7169.787	10441.61	0	60586
26	81	1211.469	2322.378	0	16970
27	81	2632.432	3982.638	0	26510
28	81	44628.11	62574.54	0	261390
29	81	4.938272	44.44444	0	400
30	81	18.08642	76.8219	0	560
31	81	7.037037	40.41796	0	350
32	81	7.962963	27.70128	0	140
33	81	454.9136	2031.062	0	18026
34	81	9.876543	56.13586	0	400
35	81	4.938272	43.88546	0	395
36	81	3.45679	15.98128	0	100
37	81	425.8519	1250.123	0	8780
38	81	4933.938	7484.367	0	38400
39	81	3903.642	8638.809	0	48260
40	81	1.234568	11.11111	0	100
41	81	116.0494	272.6017	0	1680
42	81	40.12346	113.032	0	500

Appendix B: Stata code

The stata .do file can be found on Github here.